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Does more mean less? The value of information for conservation planning under sea level rise.

Running Title: Conservation planning under sea level rise.

Authors: Rebecca K. Runting[1,2,3], Kerrie A. Wilson[1,3], Jonathan R. Rhodes[1,2]

1 ARC Centre of Excellence for Environmental Decisions, The University of Queensland, Brisbane, QLD 4072, Australia

2 The University of Queensland, School of Geography, Planning and Environmental Management, Brisbane, QLD 4072, Australia

3 The University of Queensland, School of Biological Sciences, Brisbane, QLD 4072, Australia

Corresponding Author: Rebecca Runting.

Ph: +61 7 3365 2494

Fax: +61 7 3365 1655

Email: r.runting@uq.edu.au.

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ABSTRACT

Many studies have explored the benefits of adopting more sophisticated modelling techniques or spatial data in terms of our ability to accurately predict ecosystem responses to global change. However, we currently know little about whether the improved predictions will actually lead to better conservation outcomes once the costs of gaining improved models or data are accounted for. This severely limits our ability to make strategic decisions for adaptation to global pressures, particularly in landscapes subject to dynamic change such as the coastal zone. In such landscapes, the global phenomenon of sea level rise is a critical consideration for preserving biodiversity.

Here, we address this issue in the context of making decisions about where to locate a reserve system to preserve coastal biodiversity with a limited budget. Specifically, we determined the cost-effectiveness of investing in high resolution elevation data and process-based models for predicting wetland shifts in a coastal region of South East Queensland, Australia. We evaluated the resulting priority areas for reserve selection to quantify the cost-effectiveness of investment in better quantifying biological and physical processes.

We show that, in this case, it is considerably more cost-effective to use a process-based model and high resolution elevation data, even if this requires a substantial proportion of the project budget to be expended (up to 99% in one instance). The less accurate model and dataset failed to identify areas of high conservation value, reducing the cost-effectiveness of the resultant conservation plan. This suggests that when developing conservation plans in areas where sea level rise threatens biodiversity, investing in high resolution elevation data and process-based models to predict shifts in coastal ecosystems may be highly cost-effective. A future research priority is to determine how this cost-effectiveness varies among different regions across the globe.

INTRODUCTION

Many studies have explored the benefits of adopting more sophisticated modelling techniques or spatial data in terms of our ability to accurately predict ecosystem responses to global change (Dowman 2004; Gesch 2009; Johansen *et al.* 2010). However, we currently know little about whether the improved predictions will actually lead to better conservation outcomes once the costs of gaining improved models or data are accounted for. It is not necessarily true that gaining more information leads to better decision making under global change, especially when resources must be split between the collection of information and the implementation of management actions (Nichols & Williams 2006; Grantham *et al.* 2008; McDonald-Madden *et al.* 2010; Runge *et al.* 2011; Williams *et al.* 2011). For example, Grantham *et al.* (2008) found diminishing returns from investment in survey data to inform conservation planning for Proteaceous species in South Africa. Despite this issue, little attention has been paid to the costs (i.e. financial, time, resources) of acquiring this information and the inherent trade-offs involved when it comes to implementing conservation actions (McDonald-Madden *et al.* 2010). This severely limits our ability to make strategic decisions for adaptation to global change. Understanding how much to invest in information versus management action is crucial to achieve maximum return on conservation investments (Balmford & Cowling 2006).

This is particularly pertinent in the context of a rapidly changing climate. Under these conditions, the distribution of biodiversity may be highly dynamic and is crucial to take into account when making conservation decisions (Game *et al.* 2011). This is particularly true for coastal systems, where dynamic change due to sea level rise (SLR) presents considerable challenges for developing cost-effective plans to preserve biodiversity. For instance, SLR is likely to inundate and displace wetlands and other low-lying ecosystems (Traill *et al.* 2011). This may lead to the loss of breeding grounds for diverse marine fauna, along with increased coastal flooding and erosion and saltwater intrusion into estuaries, deltas, and aquifers (McLean *et al.* 2001; Lombard *et al.* 2003; Fuentes *et al.* 2011). However, coastal wetlands may adapt to SLR by migrating landward, or increasing their vertical elevation if there is sufficient sediment supply (Nicholls & zenave 2010; Chu-Agor *et al.* 2011). To accommodate this landward migration, it may be critical to set aside areas that are free of physical barriers to the retreat of these ecosystems (Chu-Agor *et al.* 2011).

Planning to achieve the conservation of coastal ecosystems under global change is complicated by uncertainties associated with predicting the response of ecosystems to SLR. This uncertainty stems from a lack of knowledge surrounding the many interacting biophysical aspects of coastal and global systems, and how they will change in the future (McDonald-Madden *et al.* 2008;

Game *et al.* 2011; Mantyka-pringle, Martin & Rhodes 2012). For instance, before we can predict the responses of coastal systems to SLR, we must first acknowledge that there is substantial variation in the projected extent of SLR to 2100 (McLeod *et al.* 2010; Fuentes *et al.* 2011), primarily driven by the lack of knowledge surrounding future glacial melt (Hansen 2007; Meehl *et al.* 2007). As SLR is a key driver of coastal ecosystem change, variations in SLR can alter other biophysical factors influencing the response of coastal ecosystems (such as erosion and accretion rates) (Nicholls & Cazenave 2010). So as to accommodate this uncertainty, this study considers the adaptation responses of coastal ecosystems for a range of SLR projections.

Coastal impact models are useful tools for predicting environmental responses to SLR and can inform adaption plans. Approaches for modelling the response of coastal ecosystems to SLR vary in their level of intricacy and data requirements, from simplistic “bathtub” applications of SLR projections, to more involved complex models that account for hydrological processes, ecological feedbacks, and anthropogenic barriers to habitat transition dynamics (McLeod *et al.* 2010). These models differ in their complexity, but also in terms of the scale at which they are applicable, the types of ecological processes they incorporate, and with the cost and time involved in running them (Gesch 2009). Uncertainty exists around the appropriate choice of coastal impact model with different models and parameterisations producing different results (McLeod *et al.* 2010). However, the inclusion of key ecological processes in the more complex models may somewhat account for the uncertainty surrounding the response of coastal vegetation communities to SLR (Chu-Agor *et al.* 2011).

Determining SLR impacts in the intertidal zone is also highly dependent on the accuracy of the elevation data used to identify the water-land conversion zone, along with local tidal data (Gesch 2009). Resolution and accuracy is particularly important when using complex models, as minor changes in elevation (in the order of centimetres) can drive key processes in these sensitive ecosystems (Gesch 2009). The uncertainty inherent in elevation data inputs into coastal impact models can limit the accuracy of predictions and consequently their usefulness for management and planning, yet a range of elevation datasets have been used in previous studies as inputs into coastal impact models (Gesch 2009; McLeod *et al.* 2010). The horizontal resolution of these datasets ranges from a coarse resolution of approximately one kilometre, with a vertical accuracy of 5 m for regional and global studies (Reyes *et al.* 2000; Martin *et al.* 2002; Small & Nicholls 2003; Li *et al.* 2009), to a finer horizontal resolution of about 10 cm, with a vertical accuracy of 11 to 30 cm for site-specific analyses (Geselbracht *et al.* 2011; Traill *et al.* 2011). However, this fine resolution data is far more expensive to obtain and requires more expertise to apply (Johansen *et al.* 2010).

The dearth of information on the cost-effectiveness of alternative choices of models and data severely limits our ability to make strategic decisions for adaptation to global change, particularly in landscapes subject to dynamic change such as the coastal zone. Along with the global phenomenon of sea level rise, many of these systems are facing considerable development pressure, thus exacerbating the need to allocate conservation resources wisely (Game *et al.* 2011; Traill *et al.* 2011). Any additional resources allocated to higher resolution data or more sophisticated modelling of ecosystem responses to global change means there is less remaining for the implementation of management actions. Whilst adopting a more accurate approach may mean less land is acquired in terms of overall area, the land that is acquired would be of greater conservation value as the cheaper (but poorer quality) approaches tend to omit areas of important conservation value in the prioritisation process (Gesch 2009).

Despite the aforementioned uncertainties, it is not appropriate to defer decision making and planning given the urgency and severity of potential climate change impacts (Cowell *et al.* 2006). Sea level rise is a particularly critical consideration for preserving coastal biodiversity, yet many approaches for prioritising conservation networks do not take this into account (Wetzel *et al.* 2012). We advance our understanding of how to tackle this global issue by testing whether investing more resources in better quantifying both biological and physical processes can lead to better conservation outcomes when resources are limited. Specifically, we examine the development of reserve design for the conservation of coastal ecosystems in the presence of SLR. We used a section of Moreton Bay in South East Queensland, Australia as a case study to quantify the value of investing resources in complex models and high resolution elevation data for conservation planning under SLR. We found that, in this case, it was usually more cost-effective to use the complex model and high resolution dataset, even if this comprised a substantial proportion of the project budget. This remained consistent across the range of sea level rise predictions and most budget levels.

MATERIALS AND METHODS

The aim of this study was to determine if employing complex models and high resolution elevation data is cost-effective for conservation planning under sea level rise. Two coastal impact models (one process-based and one not) and two elevation datasets (one high resolution and one not) were selected for comparison. This forms four model-dataset combinations hereafter referred to as; ‘simple-coarse’, ‘simple-fine’, ‘complex-coarse’, and ‘complex-fine’ (Table 1). The ‘complex-fine’ combination was assumed to be the most accurate and was thus chosen as the benchmark dataset. The ‘complex’ model incorporates key ecosystem process and has been validated in previous studies (such as Geselbracht *et al.* 2011), and the ‘fine’ elevation dataset has a much finer spatial resolution and better vertical accuracy than the ‘coarse’ substitute. The alternate combinations of models and datasets were then applied to spatial prioritisation software (Zonation) for a range of budgets, with land acquisition as the conservation management action. The fewer resources spent on acquiring the model and datasets, the more funds that would be left to purchase land for conservation.

Study Area

The study area was located in coastal South East Queensland (SEQ), Australia, specifically latitude S27.3° to S27.5° and longitude E153.15° to E153.25° (Fig. 1). This regional planning area is of particular interest in the context of global change given its high rates of human population growth (being one of the fastest growing urban regions in Australia (Queensland Government 2008; Department of Infrastructure and Planning 2009)), with the human population increasing by an average of 2.6% per annum between June 2006 and June 2011 (Australian Bureau of Statistics 2012). Furthermore, the extensive coastal development and the existence of important coastal ecosystems mean that the issues surrounding SLR and the identification of appropriate policy responses are of great interest (Abel *et al.* 2011; Lovelock *et al.* 2011). In addition, the human settlements encompassed by the study site face socio-economic disadvantage, relative to other areas in SEQ, due in part to accessibility issues (Runting *et al.* 2011), which may be exacerbated with rising sea levels. An objective to set aside land for receding coastal ecosystems is declared in the SEQ Regional Plan 2009–2031 (Department of

Infrastructure and Planning 2009), however few details exist about how this may be achieved and an increasing number of coastal dwellings are still forecast. The size of the study site (~600km^2) was chosen to be the same order of magnitude in size as the Local Government Areas (LGAs) in the region which are the primary administration units responsible for land-use planning. This site was chosen so that it included all wetland types in the region, together with agricultural and urban areas (Traill *et al.* 2011).

Coastal Impact Models and Elevation Datasets

Coastal impact models vary in their level of complexity and accuracy, along with the cost and time involved in running them. Many studies have employed simplistic models of the effects of SLR; which approximate habitat loss from a hypothetical instantaneous SLR event (Fish *et al.* 2005; Fuentes *et al.* 2010; Traill *et al.* 2010). This approach is often referred to as an 'Inundation' model as it does not incorporate the processes of salt water intrusion, the migration of wetlands, erosion, or sedimentation (Traill *et al.* 2011). The primary advantage of the Inundation model is that it is comparatively inexpensive to run, typically requiring only SLR projections, elevation data, and GIS software (McLeod *et al.* 2010). It is also quick to produce, requiring minimal expertise, can use freely available elevation data, and can be easily understood (McLeod *et al.* 2010). Therefore, an Inundation model was used to represent the 'simple' model (Table 1).

Alternatively, more sophisticated complex models can be employed that account for dynamic processes, but require more data and expertise to apply (such as the Sea Level Affecting Marshes Model (SLAMM) (Park *et al.* 1993; Craft *et al.* 2009), the Barataria-Terrebonne ecological landscape spatial simulation model (Reyes *et al.* 2000), the Mississippi Delta Model (Penland *et* *al.* 1988), or the Dynamic Interactive Vulnerability Assessment model (Hinkel & Klein 2009). SLAMM (version 6) is an example of a more complex, process-based coastal impact model which allows for the prediction of shifts in ecosystems, due to the inclusion of some key ecological processes and abiotic factors (Craft *et al.* 2009; McLeod *et al.* 2010). However, SLAMM requires an array of additional datasets including: detailed wetland information, tidal data and accretion/erosion data (Craft *et al.* 2009). Although other process-based models exist, SLAMM was the only accessible model at the time of writing that attempted to incorporate key processes at the desired scale, hence it was used to represent the 'complex' model in this study (Table 1).

All coastal impact models require an elevation dataset to assess the impact of SLR. The National Elevation Dataset (at a resolution of 30 m) is frequently used for scientific applications in the USA (Gesch *et al.* 2002; Lombard *et al.* 2003; Aiello-Lammens *et al.* 2011). A comparable dataset for Australian applications is the 1 second Shuttle Radar Topographic Mission (SRTM) derived DEM Version 1.0 (herein referred to as "30 m DEM") (Gallant 2010). This dataset, similarly, has a 30 m grid cell size, with 90% of tested locations within 7.2 m of their gridded horizontal position (Rodriguez *et al.* 2006). The absolute elevation accuracy (relative to the stralian Height Datum 71) has a root mean square error (RMSE) of 3.87 m at the 95th percentile (Geoscience Australia 2010). This dataset was therefore used to represent the 'coarse' elevation dataset (Table 1).

A more accurate (but more costly) elevation dataset is that derived from Light Detection and Ranging (LiDAR) data. LiDAR data has a significantly better spatial resolution, which can be as little as 10 cm (Lombard *et al.* 2003; Fewtrell *et al.* 2011). There are clear advantages in using this type of data for identifying areas vulnerable to SLR, and it has been successfully used in previous studies for this purpose (Geselbracht *et al.* 2011; Traill *et al.* 2011). We derived elevation for the study area from LiDAR data provided by the Queensland Department of Environment and Resource Management, based on Airborne Laser Scanning data from 2009. This was scaled up to five metres for this analysis, which gives it a RMSE of 0.06 m at the 95% confidence level (Traill *et al.* 2011). This LiDAR data is substantially more accurate than the 3.87 m RMSE of the 'coarse' dataset (Geoscience Australia 2010). Therefore, this was used to represent the 'fine' elevation dataset (Table 1). In some locations the coarse and fine elevation datasets show considerable differences (supporting information Fig. S1).

Sea Level Rise Scenarios

To encompass the range of SLR predictions, we used a lower, mid-range, and upper SLR projection to 2100. A rise of 29 cm was used for the lower SLR estimate, based on the projections provided by the IPCC (Meehl et al. 2007). However, the IPCC predictions are not suitable for establishing a mid-range or upper projection as they do not include the contribution from ice sheet melt, despite this likely being the most important factor influencing SLR to 2100 (Meehl et al. 2007; Pilkey & Young 2009). Consequently, the mid-range projection of 1.8 m was taken from Pfeffer, Harper and O'Neel (2008), who estimate the kinematic constraints of glacial contributions, and Vermeer and Rahmstorf (2009), who link global sea level variations to global mean temperature. Finally, the upper estimate of 5 m is based on Hansen (2007)'s theory of non-linear contributions from ice sheet melt. This upper estimate is supported by studies of past interglacial periods, which show sea level to have been between three and six metres higher than present, with the climate two degrees warmer (Blanchon & Shaw 1995; Neumann & Hearty 1996; Cuffey & Marshall 2000; McCulloch & Esat 2000; Siddall *et al.* 2003; Stanford *et al.* 2006).

Additional Model Parameters

In addition to an elevation dataset and SLR projections, both models require the current spatial distribution of vegetation, wetlands and land-use. The categorisation of wetland types was based on categories for the United States National Wetland Inventory (USFWS 2011), but with the wetland communities adapted to the Australian sub-tropical context (Traill *et al.* 2011). This spatial layer includes urban areas, agricultural areas and open water, along with wetland types (specifically *Melaleuca*, mangrove and saltmarsh communities). Data on urban areas, agricultural land, beaches, rivers and ocean were collated from the Queensland Government LANDSAT mosaic imagery (30 m resolution) (DERM 2000). Areas of rocky shores were sourced from *OzCoasts* (derived from 30 m resoultion LANDSAT imagery) (Dyall *et al.* 2005) and wetlands from the Queensland Government Remnant Vegetation data (1.2 ha minimum mapable unit) (Queensland Herbarium 2009). This derived spatial layer of vegetation, wetlands and landuse was mapped at a resolution of 30 m, which aligned with the 'coarse' analysis. This derived layer was then re-sampled to a resolution of 5 m to align with the 'fine' analysis.

Additional data is required to complete the parameterisation of SLAMM. Data for accretion and shallow subsidence were based on field data measurements from Lovelock et al. (2011) and Traill et al. (2011), which varied for different wetland types and elevation. We used averaged data across the region for the net surface elevation change (i.e. accretion and shallow subsidence), which was set at 1.21 mm year^{-1} for saltmarsh (samphire/claypan) communities. The rate of surface elevation change for mangrove communities was modelled as a function of elevation within SLAMM, relative to the Australian Height Datum (AHD). At mean tide level the rate of surface elevation change was specified at -1.95 mm year^{-1}, increasing linearly to 1.03 mm year^{-1} at 0.7 m above AHD, to approximately align with the upper edge of mangroves. This is to say that SLAMM was parameterised so that mangroves will lose elevation at lower elevations, but gain at higher elevations. This might be unusual for many settings, but for Moreton Bay it is most likely occurring because root growth is low (due to nutrient pollution) and the soil is not receiving sufficient inputs to fill macropores (Lovelock et al. 2011). Data were also used from Traill *et al.* (2011) for overwash events (1 in 25 years), mean tide level (-0.01 m relative to AHD), tidal range (1.53 m), and the salt boundary (1.26 m above the mean tide level).

Spatial Prioritisation

Spatial conservation prioritisation uses quantitative techniques to generate spatial information about conservation priorities (Moilanen *et al.* 2009). It was employed in this study to answer to the question: What is the maximum conservation benefit that can be attained for different budget levels? Reserve selection was employed as the conservation management action, as this is a commonly used method for preserving biodiversity (Naidoo *et al.* 2006; Wilson *et al.* 2006; Moilanen 2007; Klein *et al.* 2009; Carroll, Dunk & Moilanen 2010). Several software packages exist (i.e. Marxan, Zonation, C-Plan, and ConsNet) that generate priorities from spatial data on relevant attributes (such as species distributions and costs) using mathematical or logical algorithms (Moilanen *et al.* 2009). Marxan (and Marxan with Zones) requires the user to parameterise how much conservation benefit they want, through the requirement of a target for each conservation feature (e.g. species) (Ball, Possingham & Watts 2009). It then selects the assemblage of units that achieve these targets for the lowest cost (Ball, Possingham & Watts 2009). However, this analysis did not necessitate a specific level of conservation benefit; instead, we required the maximum benefit possible for a specified budget. This was achievable using Zonation, which seeks to maximize the conservation benefit for the lowest cost, without requiring the user to set targets for the conservation features (e.g. number of species or ecosystems conserved) (Moilanen 2007, p. 571). This produces a hierarchy based on the iterative removal of the unit(s) with the least conservation value relative to the cost, which was ideal for this analysis (Moilanen 2007; Moilanen *et al.* 2005).

To represent the cost of reservation spatially, data on unimproved land values was sourced from the Queensland Valuation and Sales database for the terrestrial/coastal areas of the study site (DERM 2006). Whilst these data may underestimate the value of residential properties (by not including the value of built structures and the like), these residential lots were not included as a conservation feature for the Zonation algorithm to conserve. Thus they would never actually be 'purchased' for inclusion in the reserve design. These data on unimproved land values represented the spatial heterogeneity of reservation costs, which is a vital component of systematic conservation planning. Property boundaries were used as planning units for the terrestrial/coastal areas, as this is the natural resolution at which land acquisition for reservation would occur (Naidoo *et al.* 2006). Where property boundaries were absent (mainly on land adjacent to ocean or estuaries), $100m^2$ grid cells were used as planning units instead. These planning units were allocated a value close to zero, as they represented locations that were not feasible for development.

We used the Zonation software to generate priority areas for reservations based on the "maximum coverage formulation", which seeks to maximize the conservation benefit (e.g. number of species or ecosystems conserved), whilst minimising the cost (Moilanen 2007, p. 571). The 'Core Area Zonation' planning mode was selected as the objective function when running Zonation, as it operates by maximising the conservation benefit based on the area conserved, its conservation value, and the overall connectivity (see Moilanen (2007) for more information). The planning units were ranked independently for each model-dataset combination and SLR scenario, based on their ability to satisfy the objective function of Zonation.

We then used Zonation to produce the Weighted Range Size Corrected Richness (WRSCR) for each cell in the benchmark case (i.e. the 'complex-fine' combination). The WRSCR gives a higher score to cells with an abundance of rare vegetation types, relative to those containing only widespread vegetation types (refer to Nichols and Williams (2006) for more detailed information). Vegetation types are a commonly used as a proxy for biodiversity in systematic conservation planning (Carwardine *et al.* 2007; Crossman *et al.* 2007; Carboni *et al.* 2009; Adams *et al.* 2010; Lourival *et al.* 2011), and have been shown to be an effective surrogate (Payet *et al.* 2010). This gave us an approximate measure of the conservation value that would exist in 2100, and was thus used as a reference to compare the different model-dataset combinations (Fig. 2). This ensured that the different model-dataset combinations were compared to a consistent measure of conservation value (the WRSCR from the benchmark case. i.e., the complex-fine combination). In the value of information literature, when calculating the value of additional data collection, the best available existing information are assumed to provide an unbiased estimate of the true state of the system (see Ades et al. (2004), Runge et al. (2011) and Williams et al. (2011) examples from the medical and environmental decsion making literature). In addition, Grantham et al. (2008) used this approach for a conservation planning problem, in that they employed the best available model simulations to test for the cost-effectiveness of using less accurate information. Our approach is essentially analogous to these and should minimise bias in our results in the absence of knowing the true outcome for 2100.

The budget size may influence which model-dataset combination is ideal, as larger budgets can more easily absorb the higher costs of running a complex model with high resolution data. To account for this, we generated results for a series of budget levels, for each model-dataset combination and SLR scenario. One hundred and fifty different budget levels were used, based on a range of conservation budgets reported in the literature, then re-calculated for the 600km^2 area used for this study (Balmford *et al.* 2003; Murdoch *et al.* 2007; Underwood *et al.* 2008). The range of budgets selected was between $10,000 and $50,000,000 (all values are in 2011 Australian dollars), so as to encompass this range.

We then determined the maximum conservation value that can be attained by iteratively 'purchasing' the planning units (i.e. properties) in rank order until the specified budget was exhausted. This was repeated independently for all model-dataset combinations, SLR scenarios and budget levels. The resulting groups of planning units were then used to extract the benchmark conservation value of each cell, always derived from the 'complex-fine' WSRCR (Fig. 2). For example, the land parcels selected by Zonation for the simple-coarse combination were given a value that corresponds to the WRSCR of those same land parcels derived from the complex-fine combination (i.e. not the WRSCR of the simple-coarse combination). This was undertaken to determine how much conservation value would be conserved if the 'complex-fine' WSRCR was an unbiased estimate of the true conservation value in 2100.

Cost-Effectiveness

Initially, we explored the impacts of cost on our results in a theoretical way by selecting a model-dataset combination and determining how much the budget could be reduced whilst still attaining the same conservation value if another combination was used instead (Fig. 3). This was repeated for all model-dataset combinations, budget levels, and SLR scenarios, always using the WRSCR from the benchmark case as a measure of conservation value (Fig. 2). Ultimately, this shows the maximum amount that could be spent on acquiring a more accurate model-dataset combination without forgoing any conservation benefit (referred to subsequently as the break-even cost).

We then compared this break-even cost to the estimated actual cost of acquiring each model-dataset combination to assess the cost-effectiveness of each combination (Appendix S1 details the estimated actual costs). The total of the costs relevant to each of the model-dataset combinations were compared to the break-even cost. If the actual costs exceeded the break-even cost, then it was deemed not cost-effective to invest in the model-dataset combination in question and *vice versa*.

RESULTS

Overall Performance

The various model-dataset combinations produced quite different distributions of vegetation types by 2100 (Fig. 4). When no cost is attributed to any of the model-dataset combinations, greater conservation value is achieved from using the 'complex-fine' combination for the mid-range SLR scenario, irrespective of budget level (Fig. 5a). This relationship also holds for all budget levels for the upper SLR scenario (Fig. 5b), however it does not hold for smaller budgets in the lower SLR scenario (Fig. 5c). For budgets less than $12 million in the lower SLR scenario, there is some interchange between which model-dataset achieves the greatest conservation value, with the 'simple-fine' combination dominating.

Whilst the 'simple-coarse' combination consistently preserves the least conservation value under all SLR scenarios, there is a notable difference between SLR scenarios when comparing the performance of the ‘complex-coarse’ and ‘simple-fine’ combinations. In the mid-range and upper SLR scenarios the ‘complex-coarse’ combination achieves the greatest conservation value (at most budget levels), whereas the conservation value achieved with the ‘simple-fine’ combination remains low (Fig. 5a and 5b). However, in the lower SLR scenario, the ‘simple-fine’ combination achieves greater conservation value, although the results are similar for budgets larger than $30 million (Fig. 5c).

Break-Even Cost

As the overall budget increased, so did the break-even cost for each model-dataset combination, and these break-even points generally comprised a relatively large percentage of the total budget (Fig. 6). In some circumstances, it was worth spending up to 99% of the budget on acquiring the ‘complex-fine’ combination (in the upper SLR scenario). The break-even cost for the mid-range and lower SLR scenarios was also a large proportion of the total budget (with a mean of 82% and 64% respectively). The reason for this can be seen in Fig. 5b, which shows the ‘simple-coarse’ combination plateauing at a low conservation value. This same conservation value can be achieved by spending only $150,000 on land acquisition with the ‘complex-fine’ combination, compared to $50 million with the ‘simple-coarse’ combination (in the upper SLR scenario). Consequently, it is worth spending a large proportion of the budget on the ‘complex-fine’ combination. The maximum cost to run the ‘complex-fine’ combination was estimated at $722,600, which is substantially less than most of the break-even costs calculated (Appendix S1).

With access to either fine resolution elevation data or the complex model (i.e. zero cost), it was still generally worth spending a substantial proportion of the total budget on the more sophisticated model-dataset combinations (Table 2). Starting with fine resolution elevation data (i.e. zero cost), but only the Inundation model, it was worth spending up to 96% of the budget on the complex model (SLAMM). Importantly, the maximum estimated cost to run SLAMM was $122,600 (Appendix S1), which is substantially less than 96% of nearly all budget levels. Therefore, it is likely that an even greater amount of conservation value would be preserved when the complex model is used. Starting with the process-based model but only the coarse resolution DEM, it was worth spending up to 82% of the budget on the fine resolution data set. Realistic costs for LiDAR used in this study range from $30,000 to $600,000, which is much lower than 82% of most budget levels. This would again result in even more conservation value being preserved with an improvement in the quality of the elevation data.

In the absence of access to fine resolution data (such as LiDAR data), there is still the decision of which model to employ. In the mid-range SLR scenario it is more cost-effective to use the complex model for budgets larger than $13 million, otherwise, it was better to use the simpler model (Fig. 5a). Whilst this pattern was also seen in the lower and upper SLR scenarios, there was some variability in the point at which it is more cost-effective to switch models. For the upper SLR scenario, this point was at a much smaller budget ($150,000) than for the lower SLR scenario ($19 million).

Furthermore, these results indicate that it is more important to invest in the complex model than in fine resolution data for the upper and mid-range SLR scenarios (Table 2). However, the lower SLR scenario exhibits the opposite pattern, with more value being gained from investing in fine resolution data than in the complex model (Table 2). The 'complex-fine' combination is the most cost-effective for all SLR scenarios, despite variation in the cost-effectiveness of the alternative combinations.

DISCUSSION

Previous studies have made comparisons of the accuracy of models and/or data in terms of our ability to accurately predict ecosystem responses to global change (Dowman 2004; Gesch 2009; Johansen *et al.* 2010). However, this is of limited use to decision makers without an indication of the cost-effectiveness of this information in terms of the outcome of decisions made (Possingham *et al.* 2007). Any additional resources allocated to higher resolution data or more sophisticated modelling means fewer resources for the implementation of the management action. However, for conservation planning under SLR, we show that although less land area can be acquired with a fixed budget in this case, the land that is acquired still provides greater overall conservation benefits. This is an important result for the design of plans to preserve biodiversity in coastal regions subject to SLR.

Does More Mean Less?

Investing in detailed information was found to be an advisable action to take when developing a conservation adaptation plan for SLR in this context. This is consistent with the findings of Balmford and Gaston (1999) and Baxter and Possingham (2011) who found that investing in data, information and knowledge was an advisable course of action. Conversely, other studies (such as Grantham et al (2008)) found that comparable conservation value could be attained with less detailed information. However these studies were generally assessing the cost-effectiveness of gaining additional information for *interpolation* purposes (i.e. predicting the distribution of species within a constant space and time). In contrast, our study assessed the cost-effectiveness of *extrapolating* information of varying quality into a future time period (i.e. 2100). The dynamic nature of coastal systems under climate change means that the information acquired must be especially detailed in order to be ecologically appropriate. Consequently, whilst our results are not generalisable to every unique circumstance, they are likely to apply to other similar conservation planning contexts that attempt to incorporate SLR, as they will inherently involve temporally extrapolating information within a dynamic system.

Sea Level Rise Scenarios

Higher SLR scenarios generally increased the cost-effectiveness of process-based models and high resolution data, which is important to bear in mind considering the ongoing upward revision of SLR projections (Hansen 2007; Rahmstorf 2007). Higher rates of SLR meant there was a greater change in the initial vegetation distribution (relative to the low SLR scenario); hence there was a greater chance for the simple model to incorrectly predict this distribution. Conversely, in the lower SLR scenario, the use of fine resolution elevation data had the greatest bearing on producing optimal results. When dealing with very small changes in elevation of the mean sea level, the use of an accurate elevation dataset becomes even more important (Gesch 2009). Thus, utilising a process-based model is most important for mid and upper SLR scenarios, whereas acquiring high resolution data is most important for lower SLR scenarios. Despite these nuances, the process-based model with high resolution elevation data produces the optimal conservation outcome under the majority of circumstances.

Alternative Planning Contexts

Whilst these results are likely to be relevant for preserving coastal biodiversity in similar planning contexts, they may not apply in all settings. Key factors that might drive the cost-effectiveness of the model-dataset combinations include the terrain of the landscape, the diversity of vegetation types, the economic context, and the cost of the conservation action employed.

With regard to terrain; the results presented here may be of limited use in geographic areas where the impact of SLR is obvious, such as Pacific atolls where the maximum elevation is lower than the projected sea level (Perry *et al.* 2011). In such cases, it would clearly be unwise to invest in sophisticated modelling tools and elevation data. Detailed information may also be less cost-effective in areas with large tracts vegetation types relative to the land parcel size of the analysis. In this instance, the greater accuracy garnered by using fine resolution elevation data may not be relevant to the scale of the reserve design, which could increase the similarity between using coarse or fine data.

The cost-effectiveness of detailed information may shift in a different economic context (such as developing countries), where the cost of land and the purchasing power of the currency in question can be vastly different (Balmford *et al.* 2003). In addition, using an alternative management action (such as invasive species control or stewardship payments (Salafsky *et al.* 2008)) is likely to affect the cost of implementation, and may therefore alter the cost-effectiveness of the different model-dataset combinations. Further research is needed to determine what effect such changes in the economic, management, and landscape context may have.

Other Considerations

It is also important to consider some practicalities of conservation planning for SLR under a long time horizon. Modelling the distribution of wetlands well into the future means there is no 'reality' to reference the results against (as models are never a perfect description of reality (McCarthy *et al.* 2001)). Consequently, the best available model and dataset were used as the reference point, the accuracies of which have both been validated in previous studies (Gesch

2009; Geselbracht *et al.* 2011). Also, although the variation SLR scenarios did not substantially affect which model and dataset was the most cost-effective, the projected wetland distributions in 2100 for each of these scenarios were considerably different. Whilst it would be advantageous for decision makers to have more certainty about future sea levels (Nicholls & Cazenave 2010), the non-linearity of ice-sheet melt makes accurately predicting the change in sea level at a particular date unattainable at present (Hansen 2007; Meehl *et al.* 2007). Therefore, it is necessary to consider the impacts from a range of SLR projections, which is a well-established approach (Fuentes *et al.* 2010; Nicholls & Cazenave 2010; Traill *et al.* 2011). Finally, the WRSCR that we used is only one of many metrics of conservation value. Other metrics may include evolutionary refugia (Klein *et al.* 2009), beta diversity (Albouy *et al.* 2012), the probability of occurrence, or the number of endemic species (Carroll, Dunk & Moilanen 2010). It remains to be tested whether using an alternative measure of conservation value would alter our results.

Demonstrating that a particular model or elevation dataset is the most accurate does not automatically make this the optimal choice for decision making under global change. When budgets are limited, determining that such an investment is also cost-effective in terms of conservation outcomes is paramount (Naidoo *et al.* 2006). Our findings show that when designing an adaptation plan for coastal biodiversity under sea level rise, it can be more cost-effective to invest in a process-based model and high resolution dataset, even if this comprised a substantial portion of the project budget. Whilst these findings may not hold in all situations, particularly those with consistently low topographic relief or a vastly different economic context, they were consistent across a range of sea level rise predictions and budget levels. This suggests that investing a substantial proportion of the conservation budget in better quantifying both biological and physical processes can lead to better conservation outcomes when resources are limited. A future research priority is to quantify how this varies between different regions across the globe.

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SUPPORTING INFORMATION

Fig. S1: Difference in elevation between the coarse and fine elevation data.

Appendix S1: How the actual costs for each model-dataset combination were estimated.

TABLES

Table 1: Details of the model-dataset combinations we employed. Values with a * refer to the root mean square error at the 95% confidence level.

Model-dataset	*Elevation dataset name*	*Data details*	*Model name*	*Model Description*
'complex-fine' *(benchmark)*	LiDAR	5m resolution. RMSE 0.06m*. (Traill *et al.* 2011).	SLAMM	This is a complex, process-based coastal impact model which allows for the prediction of shifts in ecosystems, due to the inclusion of some key ecological processes and abiotic factors (Craft *et al.* 2009).
'complex-coarse'	30m DEM	30m resolution. RMSE 3.87m*. (Geoscience Australia 2010)	SLAMM	as above
'simple-fine'	LiDAR	as above	Inundation	A SLR projection is applied to a topographic map. Any area below the given contour is identified as being inundated. This is a cheap and fast option but it omits key ecological processes (McLeod *et al.* 2010).
'simple-coarse'	30m DEM	as above	Inundation	as above

Table 2: Mean break-even expenditure, as a percentage of the total budget for the complex model or fine resolution elevation data. SD refers to the standard deviation.

SLR scenario: / *Investment:*	**Upper**	**Mid-range**	**Lower**
Mean % to spend on the complex model *(already have fine resolution data)*	96% (SD 2%)	69% (SD 24%)	39% (SD 27%)
Mean % to spend on fine resolution data *(already have a complex model)*	82% (SD 7%)	59% (SD 25%)	70% (SD 14%)

Figure Legends

Fig. 1: Location of the study site.

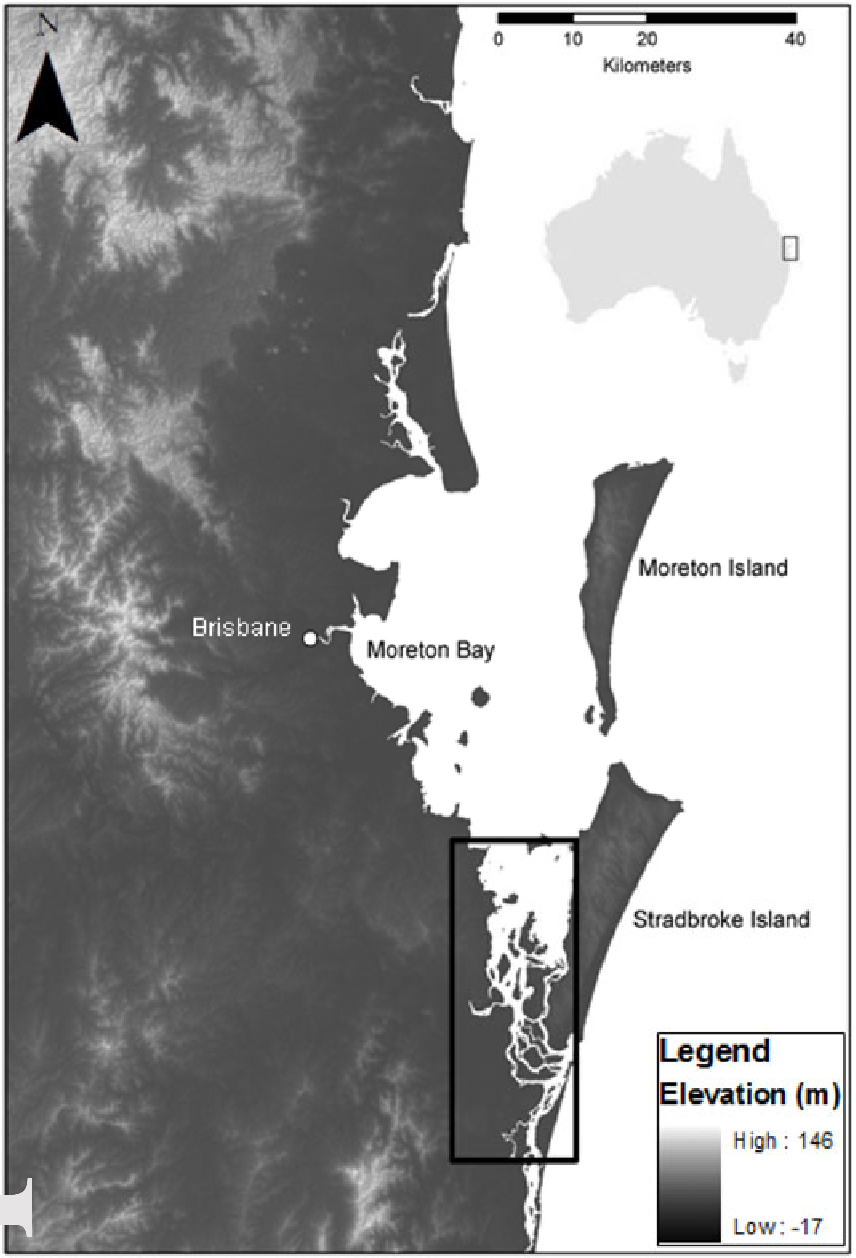
Fig. 2: Diagram of the methodology used to compare the model-dataset combinations.

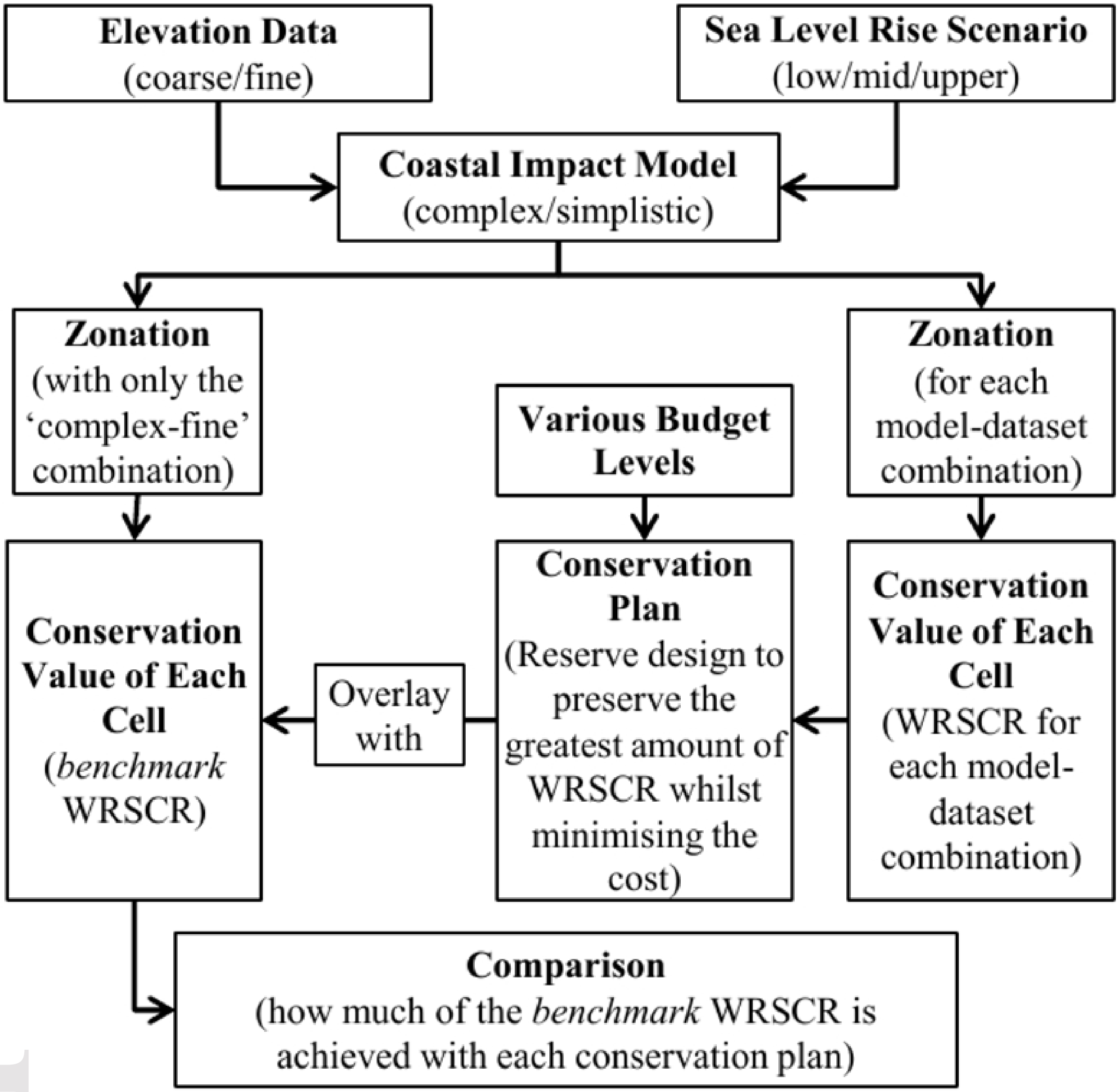
Fig. 3: Graphical representation of how the 'break-even' cost is determined. The lines represent the (hypothetical) conservation value attained at each budget level for two alternative model-dataset combinations. Zero cost is assumed for each combination. b_1 is the selected budget level for 'model-dataset 1', and c is the conservation value that can be attained for this budget level and model-dataset combination. b_2 corresponds to the budget level in which the same conservation value (c) is be achieved using an alternative combination ('model-dataset 2'). The arrow (b_1 to b_2), represents the 'break-even' cost for employing 'model-dataset 2' relative to 'model-dataset 1', given the budget level b_1. This represents how much the overall budget could be reduced whilst still attaining the same conservation value by using 'model-dataset 2'.

Fig. 4: Wetland distribution produced from the (a) 'complex-fine' and (b) 'simple-coarse' combinations for a SLR of 1.8m by 2100.

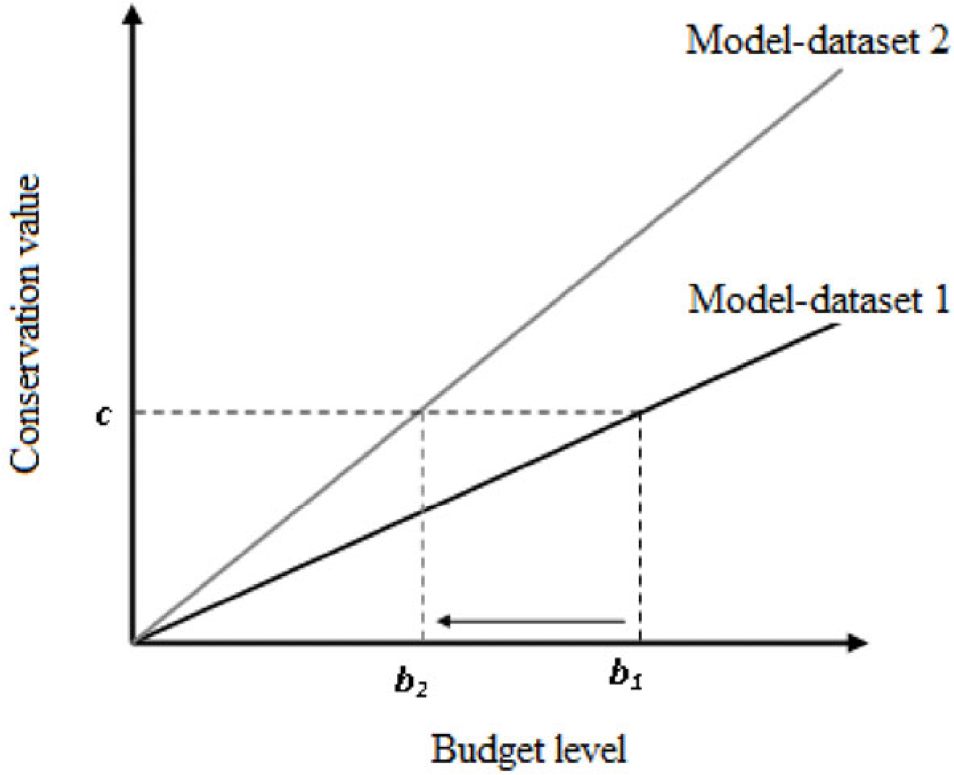
Fig. 5: The conservation value of all model-dataset combinations at zero cost for all SLR scenarios: a) mid-range, b) upper, and c) lower. A polynomial trendline fitted to the individual data points. Conservation value is represented by the "Weighted Range Size Corrected Richness" from the benchmark case (see methods).

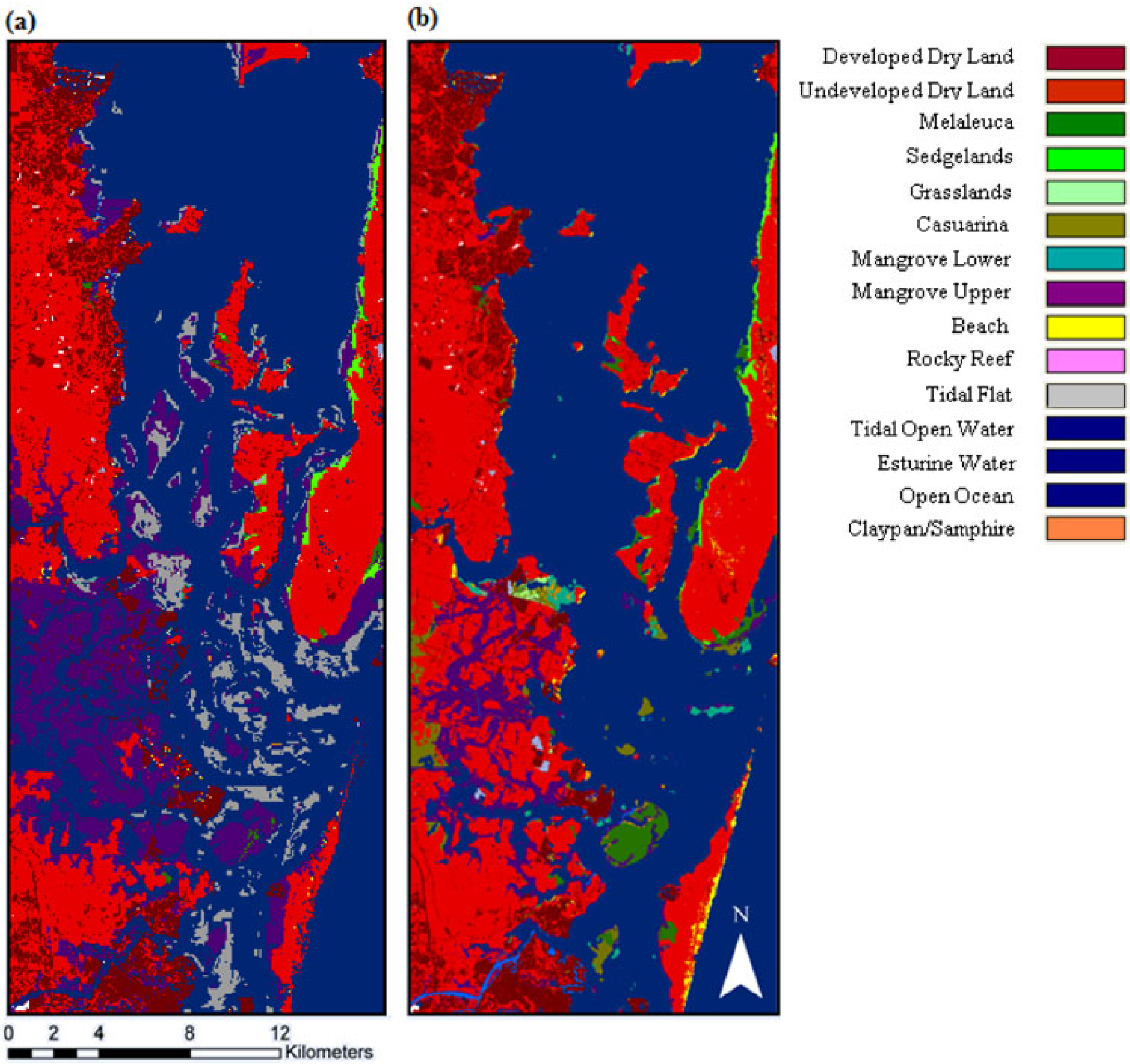
Fig. 6: The 'break-even' cost for acquiring the 'complex-fine' combination for each SLR scenario. A polynomial trendline is fitted to the data points.

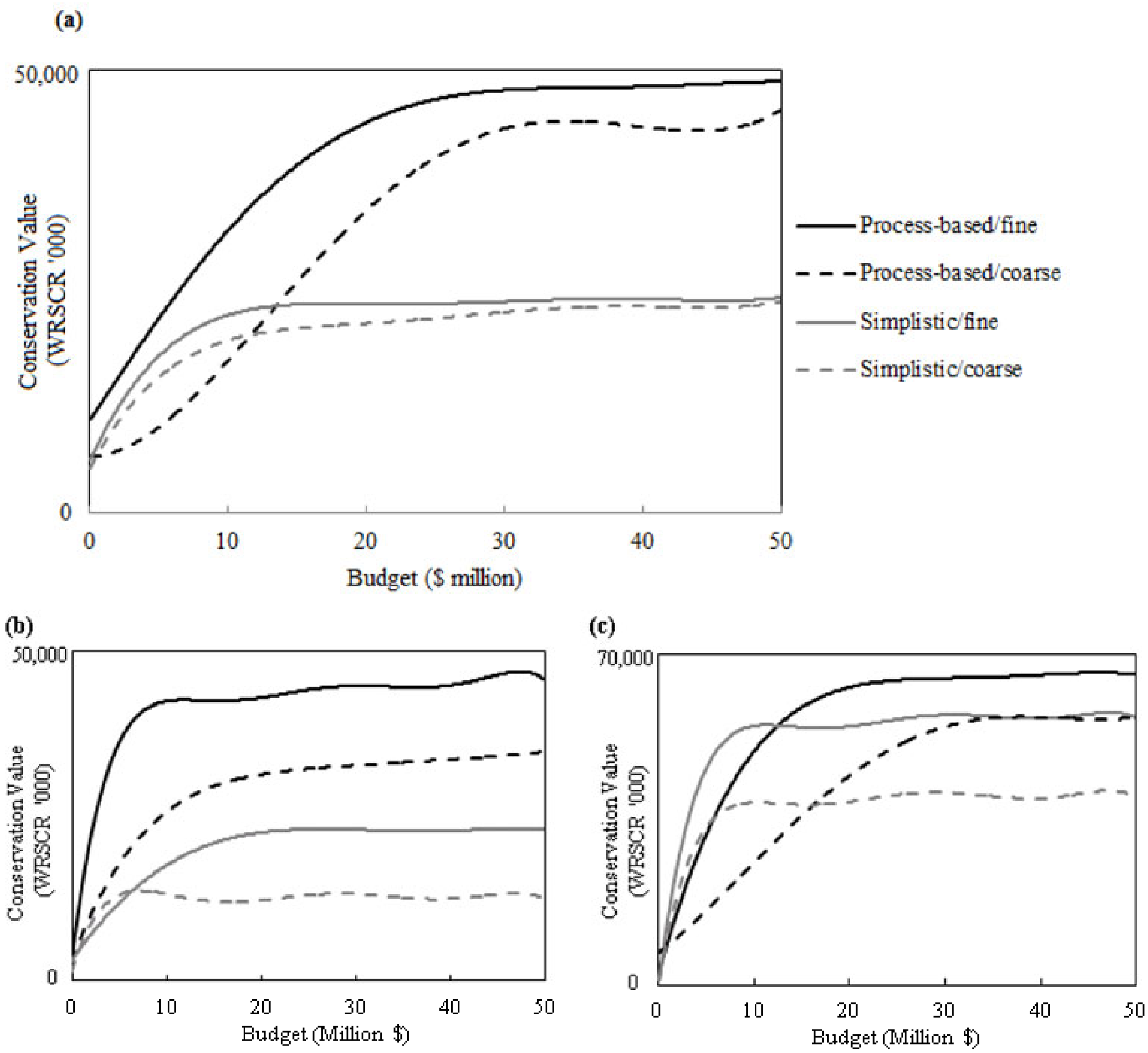

N
0
10
20
40
Kilometers
Brisbane
Moreton Bay
Moreton Island
Stradbroke Island
Legend
Elevation (m)
High : 146
Low : -17

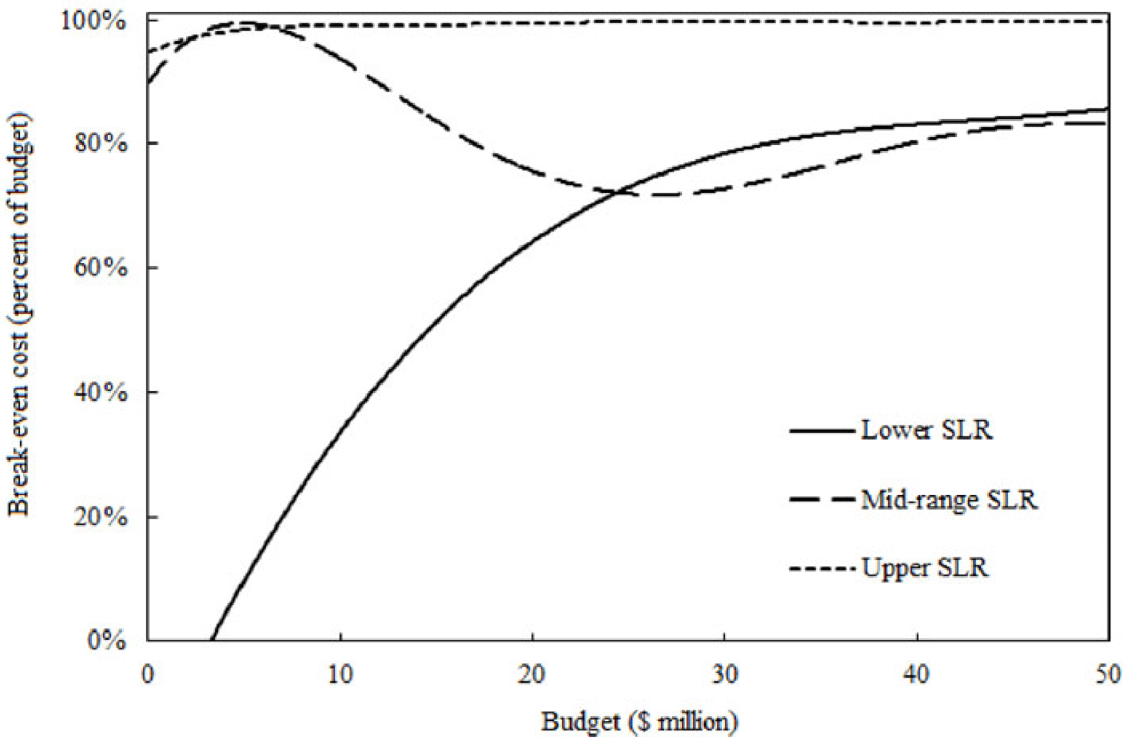


Elevation Data
(coarse/fine)
Sea Level Rise Scenario
(low/mid/upper)
Coastal Impact Model
(complex/simplistic)
Zonation
(with only the 'complex-fine' combination)
Various Budget Levels
Zonation
(for each model-dataset combination)
Conservation Value of Each Cell
(*benchmark* WRSCR)
Overlay with
Conservation Plan
(Reserve design to preserve the greatest amount of WRSCR whilst minimising the cost)
Conservation Value of Each Cell
(WRSCR for each model-dataset combination)
Comparison
(how much of the *benchmark* WRSCR is achieved with each conservation plan)


Model-dataset 2
Model-dataset 1
Conservation value
c
b2
b1
Budget level


(a)
(b)
Developed Dry Land
Undeveloped Dry Land
Melaleuca
Sedgelands
Grasslands
Casuarina
Mangrove Lower
Mangrove Upper
Beach
Rocky Reef
Tidal Flat
Tidal Open Water
Esturine Water
Open Ocean
Claypan/Samphire
N
0 2 4 8 12
Kilometers


(a)
50,000
0
0
10
20
30
40
50
Conservation Value (WRSCR '000)
Budget ($ million)
Process-based/fine
Process-based/coarse
Simplistic/fine
Simplistic/coarse
(b)
50,000
0
Conservation Value (WRSCR '000)
Budget (Million $)
(c)
70,000
0
Conservation Value (WRSCR '000)
Budget (Million $)



100%
80%
60%
40%
20%
0%
Break-even cost (percent of budget)
0
10
20
30
40
50
Budget ($ million)
Lower SLR
Mid-range SLR
Upper SLR